FPGA Implementation of Electrooculogram using Discrete Wavelet Transform

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Abstract

Neurological disorders affect about five percent of the population. Approximately one percent of this group has been found to be epileptic. Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures. These seizures are due to abnormal, excessive, episodic neuronal activity in the eyes. Diagnosis of epilepsy calls for long-term video EOG monitoring. This technique is not routinely used because of its high cost and inconvenience to the subject as the subject has to be in the hospital for longer time (typically one week to 10 days). Electrooculogram (EOG) is an important tool in the diagnosis of certain neurological disorders. The ability of the wavelet transform to capture the signal energy in a few transform coefficients and provide time and frequency information from the transient signal make it a very attractive tool for signal processing applications in several fields. In other words, The Discrete Wavelet Transform (DWT) has gained the reputation of being a very effective signal analysis tool for many practical applications. However, due to its computation intensive nature, current implementations of the transform fall short of meeting real-time processing requirements of most applications. This paper describes implementation of the Electrooculogram data using Discrete Wavelet Transform and it's inverse.

Keywords: Electrooculogram, Epilepsy, Discrete Wavelet Transform, Analysis and Synthesis filters

Introduction

One of the most developing researches in Engineering that utilizes the extensive research in medicine is Biomedical Engineering. This area seeks to help and improve our everyday life by applying engineering and medical knowledge with the growing power of computers. The computers are efficient, straight forward and never get tired or sick, while humans though are smart and creative, become sick, weak and limited. Communication between humans seem usually much simple than the one involves humans and machines. This difficulty increases when a person is disabled. However, especially this kind of people has more to gain by assisting a machine in their everyday life.

The eye is a seat of a steady electric potential field that is quite unrelated to light stimulation. In fact, this field may be detected with the eye in total darkness and/or with the eyes closed. It can be described as a fixed dipole with positive pole at the cornea and negative pole at the retina. The magnitude of this corneoretinal potential is in the range 0.4-1.0 mV. It is not generated by excitable tissue but, rather, is attributed to the higher metabolic rate in the retina. The polarity of this potential difference in the eyes of invertebrates is opposite to that of vertebrates. This potential difference and the rotation of the eye are the basis for a signal measured at a pair of periorbital surface electrodes. The signal is known as the electrooculogram, (EOG) which is useful in the study of eye movement.

Electrooculogram (EOG) is a valuable diagnostic tool in medicine and is useful in the diagnosis of the Parkinson's disease, epilepsy, etc. In addition, EOG analysis can deliver significant information to quantitatively identify the sleep status, eye injury; etc. EOG analysis would also support the research in intelligent robot and assisted tools for the disabled [1]. The study has been found to be time consuming, tedious and inefficient. Application of digital processing techniques to the recorded data or real time data results in helping the neurologist in speedy and accurate diagnosis in addition to data compression and ease of transmission for remote diagnosis [2-4]. These techniques help in reviewing the records quickly, reduce human error making the expert neurologists' services available to a larger populace. A powerful theory was proposed in late 1980's to perform time -scale analysis of signals: the wavelet theory. This theory provides a unified framework for different techniques which have been developed for various applications [5]. The Wavelet Transform (WT) is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis. Hence the WT is well suited to locating transient events such as spikes, which occur during epileptic seizures. The authors in their previous work demonstrated the use of Continuous Wavelet Transforms in Epilepsy detection and its performance [6]. Now in the present analysis DWT is implemented. The aim of this work is to classify normal and epileptic subjects based on Discrete Wavelet Transform (DWT) and to implement this using a digital signal processor (DSP).

Materials

The Electrooculography (EOG) is a measurement of bio potentials produced by changes in eye position. The fact that electrical activity could be recorded by placing electrodes on the surface of the skin in the eye region was discovered in the 1920's. It was realized that the electrical potentials induced corresponded (almost linearly) to eye movement. It is now accepted that the generated electrical potentials arise due to the permanent potential difference of between 10 to 30mV that exists between the cornea and the ocular fundus. This is commonly referred to as the cornea-retinal potential with the cornea being positive. An electrical field is set up in the tissues surrounding the eye and rotation of the eye causes a corresponding rotation of the field vector. The EOG is one of the very few methods for recording eye movements that does not require a direct attachment to the eye itself. For this reason, the EOG technique is preferred for recording eye movements in sleep and dream research and when recording eye movements in infants. Recently, this technique has become popular for evaluating reading ability and visual fatigue of subjects.

If the orientation of the eyes is measured, it is possible to locate the 3D position of a fixated target object by triangulation. The accuracy of the location determination depends on the accuracy with which the eye orientation is determined. In this respect, EOG cannot compete with the direct reflectance methods. In EOG, a quantitative estimate of positional accuracy can be based on the observation that there is a change in potential of about 5-20 micro volt for every degree of change in eye orientation in either direction. Thus accuracy and resolution are determined by the sophistication of the electronic circuitry (and hence also its cost) built to amplify and condition this signal. By placing electrodes superior and inferior to the orbit of each eye, and a reference electrode lateral to the eye of interest, vertical eye movements can also be measured. When a test subject is gazing straight ahead, the corneal-retinal dipole is symmetric between the two electrodes, and measured EOG output is zero. As the subject gazes to the left, the cornea becomes closer to the left lateral electrode, therefore causing the EOG output to become more positive. The inverse of this is true when the subject looks in the right direction. As mentioned before, when measuring the EOG output, there is a fairly linear relationship between the horizontal angle of gaze and the EOG output. This relationship remains true up to approximately thirty degrees of arc.

The original EOG data in epileptic and normal situation is provided by Nizam Institute of Medical Sciences (NIMS), Hyderabad.

Method

Wavelet Transform Algorithm

The problem of an adequate interpretation of epileptic EOG recordings is of great importance in the understanding, recognition and treatment of epilepsy. Wavelet theory provides a unified framework for a number of techniques developed for various signal processing applications like detection of unknown transient signals [79]. The Discrete Wavelet Transform (DWT) is simply a sampled version of the Continuous Wavelet Transform (CWT) [10, 11], and the information it provides is highly redundant as far as the reconstruction of the signal is concerned. This redundancy, on the other hand, requires a significant amount of computation time and resources. DWT, on the other hand, provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time.

The DWT means choosing subsets of the scales a and position b of the mother wavelet ψ (t)

$$\psi$$
 (a, b) (t) = 2a/2 ψ (2-a/2 (t-b)) \rightarrow eq. 1

Choosing scales and positions are based on powers of two, which are called dyadic scales and positions {a j =2-j; b j, k =2-j k } (j and k are integers). Eq. (1) shows that it is possible to build a wavelet for any function by dilating a function ψ (t) with a coefficient 2j, and translating the resulting function on a grid whose interval is proportional to 2-j. Contracted (compressed) versions of the wavelet function match the high-frequency components, while dilated (stretched) versions match the low-frequency components. Then, by correlating the original signal with wavelet functions of different sizes, the details of the signal can be obtained at several scales. These correlations with the different wavelet functions can be arranged in a hierarchical scheme called multi-resolution decomposition. The multi-resolution decomposition algorithm separates the signal into "details" at different scales and a coarser representation of the signal named "approximation" [7-10].

The algorithm of the DWT decomposition and reconstruction can be summarized by following procedure:

Consider an EOG signal x(n) of length n, starting from x(n), the first step produces two sets of coefficients: approximation coefficients *a*1 and detail coefficients *d*1. These vectors are obtained by convolving x(n) with the low-pass filter for approximation and with the high-pass filter for detail, followed by dyadic decimation. This is shown in Fig. 1. The length of each filter is equal to 2N. If n = length (x (n)), the signals F and G are of length n + 2N - 1, and then the coefficients *a*1 and *d*1 are of length

Floor
$$((n-1)/2) + N \rightarrow eq. 2$$

The approximation coefficients are further decomposed into two parts using the same scheme, replacing s by a1 and producing a2 and d2 and so on. So, the wavelet decomposition of the signal s analyzed at level i has the following structure: [ai, di... d1]. Conversely, starting from ai and di, the Inverse Discrete Wavelet Transform (IDWT) reconstructs ai -1, inverting the decomposition step by inserting zeros and convolving the results with the reconstruction filters, as shown in Fig. 1. Fourier analysis is extremely useful for data analysis, as it breaks down a signal into constituent sinusoids of different frequencies. The Fast Fourier transform (FFT) is an efficient algorithm for computing the DFT of a sequence.



Figure 1: The algorithm of the DWT/IDWT for one level Decomposition

Field Programmable Gate Arrays

Field programmable gate Arrays (FPGA's) now possess sufficient performance and logic capacity to implement a number of digital signal processing (DSP) algorithms effectively. The DSP algorithms can be implemented in an FPGA with levels of performance unattainable using a traditional single-chip processor [12]. The specific system simulator used in this investigation is Simulink [13], which runs within the MATLAB programming environment [14]. The design parameters relating to the DWT are entered in the Simulink block and passed to the HDL generic map and port map in the elaboration process. In this flow a parameterized DWT HDL design has been completed and only needs to be instantiated by the elaborator. In a similar flow the IDWT design process can take place.

Results and Discussions

The EOG off-line data of both normal and epileptic subjects are used in this analysis. In the current analysis 16 samples of the EOG data are considered and its DWT coefficients are computed for all 4 channels. These four channels are considered because it is concluded in the paper [15], that only 4 electrode positions are sufficient for classifying the subject.

In this case, a two-level multi-resolution decomposition using db8 wavelet is implemented. The original signal x(n) can be reconstructed by the process of IDWT. The input samples are being processed using discrete wavelet transform with the help of MODELSIM software environment. Selection of filter coefficients is being done using Matlab wavelet toolbox.

Decomposition of EOG data

The analysis procedure using EOG samples & filter coefficients are shown below The Shifted EOG Samples are:

X={12,1B,18,12,12,1A,25,25,1B,19,1F,2A,2B,25,1F,24}

The Shifted scaling coefficients are:

h0=FF h1=04 h2=03 h3=E9 h4=FD h5=50 h5=5B h7=1D

The Shifted wavelet coefficients are:

The input data is fed and convolution is performed between the above coefficients and the input data. The results are displayed in the command window Fig.2.

Current Simulation Time: 2010 ns		200 ns 400 ns 600 ns 800 ns 1000 ns 1200 ns 1400 ns 1600 ns 1800 ns
■ ■4 x[0:15]	{8	C [8h12 8h18 8h18 8h14 8h12 8h1A 8h26 8h26 8h18 8h19 8h1F 8h2A 8h2B 8h25 8h1F 8h24 C anput Samples
■ ■ 1 h[0:7]	{8	[8hFF 8h04 8h03 8hE9 8hFD 8h50 8h58 8h1D] DB4 LPF Filter Coefficients
a 🖬 (g[0:7]	{8	(8h 1D 8h A5 8h 50 8h 03 8h E9 8h FD 8h 01) DB4 HPF Filter Coefficient
□ ■ III y 1[0:7]	{8	[8h24 8h19 8h29 8h30 8h24 8h3A 8h34 8h27] Decomposed Data of Stage1
D1 yh1[0:7]	{8	(8hFC 8h06 8hFD 8h01 8h02 8h0A 8h00 8h02)

Figure 2: Synthesis waveform for I stage decomposition

The decomposed data is as follows: LPF Decomposed outputs are:

yl1 = {24, 17, 29, 30, 24, 3A, 34, 27}

HPF Decomposed outputs are:

yh1 = {FC,05,FD,01,02,0A,FF,01}

Reconstruction of EOG data:

During reconstruction, the decomposed data is being taken as input and the reverse process is done using the same filter coefficients as selected earlier. The synthesis waveform for the first stage reconstruction generated is shown in Fig.3.

Current Simulation Time: 1010 ns		Original Data Reconstructed Data
		100 ns 200 ns 300 ns 400 ns 500 ns 600 ns 700 ns 800 ns 900 ns
🖬 🏬 x[0:15]	{8	38 h12 8 h18 8 h18 8 h14 8 h12 8 h14 8 h26 8 h26 8 h18 8 h19 8 h17 8 h24 8 h25 8 h15 8 h24 3 h25 8 h17 8 h24 3
🖬 🛃 yis[0:7]	{8	(8h23 8h18 8h28 8h30 8h23 8h39 8h32 8h26) Input Data to the Reconstruction
🖬 📑 yhs[0:7]	{8	(8hFC 8h06 8hFD 8h01 8h02 8h0A 8h00 8h02) stage3
🖬 💽 xs[0:15]	{8	38h11 8h1A 8h16 8h12 8h11 8h19 8h23 8h24 8h1B 8h17 8h10 8h28 8h29 8h22 8h10 8h21
🖬 😽 h[0:7]	{8	(8hFF 8h04 8h03 8hE9 8hFD 8h50 8h5B 8h1D) DB4 Filter Coefficients of LPF &
🖬 🚮 g[0:7]	{8	(8h1D 8hA5 8h50 8h03 8hE9 8hFD 8h01)

Figure 3: Synthesis waveform for last stage reconstruction

The results of reconstruction are given below which are same as that of VHDL generated outputs for the first stage.

The Reconstruction outputs are:

Xs = {10, 19, 15, 10, 10, 17, 22, 23, 19, 17, 1B, 27, 28, 21, 1C, 21}

Hence, the values of first stage results have been verified and the values are cumulated.

Conclusions

The EOG data compression is necessary to speed up the process so that we can recognize the disabilities of the patient as soon as possible. This method has been implemented useful for compressing the data and to increase the accuracy compared with the other languages. By increasing the precision the accuracy of data after reconstruction can be obtained. This analysis serves as a handy tool in streams of engineering and medical sciences to know the behavior of a subject (human eye).

References

- [1] Chi-Wen Hsieh et.al, "The Study of the Relationship between Electrooculogram and the Features of Closed eye Motion", Proceedings of the 5th International conference on Information technology and Application in Biomedicine, Shenzhen, China, May 30-31, 2008.
- [2] Jean Gotmann, "Automatic Detection of Seizures and Spikes", Journal of Clinical Neuro Physiology, 16, 1999, pp 130-140.
- [3] Scott B.Wilson and Ronald Emerson, "Spike Detection: A Review and Comparison of Algorithms", Journal of Clinical Neurophysiology, 113, 2002, pp 1873-1881.
- [4] Clement C.C Pang, Adrian R.M Upton, "A Comparison of Algorithms for Detection of Spikes in the Electroencephalogram", IEEE Transactions on Biomedical Engineering, 50, 2003, pp 521-526.
- [5] Didier clarencon, Marc Renaudin et.al, "Real-time spike detection in EEG signals using the wavelet transform and a dedicated digital signal processor card", Journal of Neuroscience Methods Vol.70, 1996,pp5-14.
- [6] Y. Padma Sai, Dr.K.Subba Rao, et al. "Detection of Epileptic Seizures using Wavelet Transform", International Journal of Biomedical Engineering and Consumer Health Informatics, Vol. 1, No. 1, 2008, pp 15-22.
- [7] Samir V.Mehta, "Wavelet Analysis as a Potential Tool for Seizure Detection", IEEE, 1999.
- [8] Michael Unser, "Wavelets, Statistics and Biomedical Applications", IEEE 1996, pp 244-249.
- [9] Olivier Rioul and Pierre Duhamel, "Fast Algorithms for Discrete and Continuous Wavelet Transforms", IEEE Transactions on Information Theory, Vol.38, No.2, March 1992, pp 569-586.
- [10] Stephane Mallat, "A Wavelet Tour of Signal Processing", 2nd Edition, Academic Press, 1999.
- [11] Michael Unser and Akram Aldrobi, "A Review of Wavelets in Biomedical Applications", Proceedings of the IEEE, Vol.84, No.4, April 1996, pp 626-638.

- [12] Dick,C. and Krikorian,Y., "A System Level Design Approach for FPGA-Based DSP Implementations", DSP World, Spring 1999.
- [13] Mathworks, Inc., "Simulink 3.0", http://www.mathworks.com/products/Simulink
- [14] Mathworks, Inc.,"Matlab5.3", http://www.mathworks.com/products/matlab.
- [15] Y. Padmasai, K. SubbaRao, et al, "EEG Analysis using Chi Square Association metric", IETE Journal of Research, Vol. 54, No. 1, January-February 2008, pp 73-80.

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